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Computer Vision System Coupled with an Artificial Neural Network to Quality Evaluation of Rainbow Trout Eggs

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Rainbow trout in most of the proliferation and breeding sites of cold-water fishes has been propagated and inbred. One of the proliferation steps of this type of fishes is the separating fertile and living fish eggs from the infertile or dead ones and counting them for sale. In spite of various apparatuses and methods of proliferation, the recognition of fertile from dead fish eggs is essential. In this study the ability of machine vision system coupled with soft computing methods such as Artificial Neural Networks (ANN) was examined to quality assessment of fish eggs. In this regard, the captured images were transferred to the LAB color domain, because this domain is less affected by the camera and lighting conditions then several color and textural features were extracted from the images of rainbow trout fish eggs. Finally extracted features were introduced to ANN as an input layer. As a conclusion results showed that with an optimum adjustment of ANN, the alive and dead fish eggs were classified with 99% accuracy. The outcome of this investigation can be used in the fish egg quality assessment.

Keywords: Fish eggs, Image Processing, Texture Analysis, Color Analysis, Artificial Neural Network

INTRODUCTION

Traditionally, the separation of the dead eggs from the alive fish eggs has been performing manually. Currently, some semi-automated apparatuses for separating and counting of fish eggs are also available. Most of such devices are slow in operation and low accuracy. This is mainly because of their unsuitable and old technology. Moreover, they need to be supervised by some operators to increase the accuracy of separation and complete their job. Due to the inherent characteristics and unique advantages of image processing techniques it can be adapted for fish industry, specifically for fish eggs evaluation such as counting and sorting process. Also the fish egg separator devices equipped with image processing technology will have fewer repair and maintenance problems compared to the devices and methods using light and optics to separate the dead and alive fish eggs (Skala, 2005). Such devices can also benefit from computer programming and pattern recognition methods to control the system.

A basic machine vision system consists of an image-capturing device, the appropriate computer hardware and software, and a lighting system. Quality of the captured image can be greatly affected by the lighting conditions and a high quality image can help to reduce the time and complexity of the subsequent image processing steps (Du and Sun, 2004, 2006).For rapid prototyping of a machine vision system, artificial intelligence programming can be incorporated into the system. Novel tools such as artificial neural networks and fuzzy logic as expert systems can be applied to learn meaningful or nontrivial relationships automatically in a set of training data and produce a generalization of these relationships that can be used to interpret new, previously unseen test data (Mitchell et al. 1996).

The so called machine vision system is increasingly employed in various branches of science and technology. This technique can be utilized to replace visual assessment of many agricultural and food materials for different purpose of quality assessment and characterization (Yud-Ren et al. 2002, Yam et al. 2004,Kiani&Jafari, 2012).As examples, Zhao-Yan and Fang (2005)attempted to identify some rice varieties, using image processing and incorporating neural network techniques. From the images of the varieties, 7color features and 9morphological features were extracted. For each variety 200 samples were selected for network training and 60 samples were used for testing the network. Finally, they presented that the classification accuracy with this algorithm is about 88%. Because of this classification accuracy was under laboratory setting and had some limited they offer that in future work, a large quantity of rice seeds, will be investigated.

Pydipatiet al.(2006) examined the quality of seeds and fruit using machine vision system. They used some structural properties of leaf color for recognizing citrus disease. Also Abbasgholipour et al. (2010) determined a system for grading healthy raisin from unhealthy using image processing technique.

Early work in the area of image processing for beef grading based on reflectance characteristics, was done in the early 1990s (McDonald and Chen, 1990).They presented that muscle tissue was successfully discriminated from fat by generating and processing binary images of the muscle. Also Larrain et al. 2008 and Valous et al (2009) presented that by using computer vision system it was capable to extract some color features of meat for its quality evaluation

In the case of fish, machine vision has demonstrated its potential for automation of several operations in fish processing. Sizing, weighing, counting, grading, classification, recognition, and monitoring are some of the applications of machine vision in fishery industries (Quevedo et al., 2010, Gumuset al., 2011 and Dowlati et al., 2012).

Ibrahim et al. 2000 employed this technique for classifying and dirt inspecting of eggs. They presented that this technique and designed system can classify the eggs with the accuracy of 80 to 90 percent on the basis of the respective grade and this system can also successfully specify the cleanliness of the eggs. Also Dehrouyehl et al. (2010) presented an algorithms based on image processing for detecting the dirt of the eggshell and internal blood spots. They used a machine vision system in HSI color space. Blood spots detection was used from hue histogram and defect detection were selected from maximum value of two ends of the histogram. They created a hardware system include roller conveys, illumination box, camera and PC that transform the egg images to the MATLB software. At least with an average of 85.66% accuracy, their algorithms detected eggs defect. In other work, Lunadeiet al (2012) developed an off-line system based on image processing and artificial vision that automatically detected defective eggshells. They used MATLAB software for analyzing images to classify samples as clean and dirty. Eliminated the background, detection of the dirt stain and classification were three steps of their work. The algorithm classified eggs correctly nearly 98% with a fairly short time (0.05 s).

According to what have been stated above, it has been proved that image color and texture information can be utilized for the objective quality assessment of many types of food products with various applications ranging from fruits, grains, vegetables to meats and fish and many others that have been reported by (Sliwinska et al., 2014; Chen et al. 2015).Despite extensive existing research works regarding to employing machine vision system on the literature, unfortunately, computer vision has not been developed for inspection and grading of fish egg. Thus in this study, image processing techniques coupled with an artificial neural network have been applied to determine and separate the alive and dead fish eggs of rainbow trout.

MATERIAL AND METHODS

Image acquisition

To get the best result, 200 photos (100 photos of alive fish eggs and 100 photos of dead ones) were captured. These images were collected from the Ghezeldanesh fish proliferation and breeding farmin Nahavandregion, Hamedan, Iran. Image capturing was done in April 2014 with a Canon Digital Asus 500 VHS. Since the fish eggs were small, the size of images was selected to

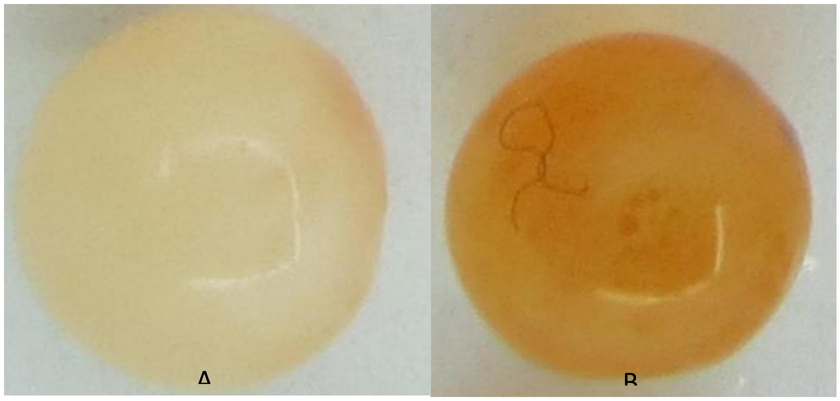

Figure 1. Samples of rainbow trout eggs, A) a dead and B) alive fish egg.

Table 1. The statistical features of the LAB color domain

Statistic	Formula
Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
Standard deviation	$std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$
Range	$range = \sqrt{(x_{max} - x_{min})^2 + (y_{max} - y_{min})^2}$

280*280pixels. To analyze the images, a PC Pentium 5 tooling with MATLAB software, with image processing and neural networks toolbox, was used. As an example, Figure 1 shows a sample of a dead and an alive fish egg. To get the best result, the Camera was fixed at 40 cm above the plate containing the samples.

Feature extraction

For each images of the fish egg samples, 26 features were extracted. Nine of them were from color features (mean, rang and standard deviation for every element of LAB) and seventeen of them were texture features. Texture features included 5 Gray Level Co-occurrence Matrix (GLCM) features (energy, contrast, correlation, homogeneity and entropy), 6 Local binary pattern (LBP) features and 6 Fuzzy local binary pattern (FLBP) features (mean, smoothness, skewness, kurtosis, entropy and standard deviation).

Color Features

Before processing of the images, backgrounds of them were omitted. The RGB color space is formed from three color components: red, green and blue. Since this color space is strongly affected by imaging instrument and condition, in this work the RGB color space transferred to LAB space. Unlike the RGB, this system is similar to the human eye. Also it does not affected by the instrument (Shafieeet al. 2014). In this space, L is the equivalent brightness, A has an unlimited amount such that the positive values represent the red and the negative values are green. The positive value of B is equal to yellow and the negative equal to blue. Today, for the majority of researches related to the food industry, LAB space is used frequently (Katherine et al. 2006). For this purpose statistical properties were extracted. These features are shown in table 1. For each element of the LAB space, the statistical properties were extracted and therefore totally nine color features were provided.

Texture's Features

For analysis of each image based on texture features, they were converted from a color images into a gray level images and then functions GLCM, LBP, and FLBP have been applied to extract texture features from them.

Table 2. Features extracted from GLCM function

Statistic	Formula
Energy	$\sum c^2(i,j)$
Contrast	$\frac{\sum_{i,j}(i-j)^2 * (i,j)}{(j-1)^2}$
Entropy	$\sum_{i,j} c_{i,j} \times \log_2 c_{i,j}$
Homogeneity	$\sum \frac{1}{i+(i-j)^2} c(i,j)$
Coloration	$\frac{\mathrm{cov}(i,j)^1}{\mathrm{std}(i) * \mathrm{std}(j)}$

a

103	100	78
97	98	101
100	90	91

b

1	1	0
0		1
1	0	0

c

1	2	4
8		16
32	64	128

d

1	2	0
0		16
32	0	0

Figure 2. LBP calculation, a: a sample neighborhood, b: resulting Bit-String, c: LBP mask and d: b*c; LBP=1+2+16+32= 49

- **Gray Level Co-occurrence Matrix (GLCM)**

In this method, the images were converted into a two-dimensional matrix as a GLCM, where each element was the probability of getting color intensity i and j in the neighborhood of the distance d and the angle θ (0^0, 45^0, 90^0, 135^0). Finally, by using of the function, similarities that are shown in table 2, five features were extracted. Before calculating the function on the co-occurrence matrix, each element of the matrix should be normalized. Data were normalized by dividing each element by the total numbers of pairs of pixels considered. From the co-occurrence matrix, first time (Haralick et al., 1973) used to extract texture features of images to troubleshoot from grapefruit. However the amount of pixels to be closer together, more concentration on the main diagonal matrix will be created in comparison to a simple histogram of pixels in the location information, is lost and only the frequency of pixel gray values is calculated and location of the pixel matrix are considered. So that the wider distribution of gray values, the variance will be seen more in the matrix.

- **Local binary pattern (LBP)**

One of the effective methods in the texture analysis is LBP. In this method, the most important properties include ease of computation and tolerance against illumination changes (Pietikainenet al. 2005). For each image, a 3×3 neighborhood was considered. For them, central pixel is a threshold. If the value of the element was greater than the value of the central pixel, the new value becomes one, otherwise it will be zero. New value of 3×3 matrix element will be zero or one. By multiple threshold neighborhood values and by resulting bit matrix, the numbers will be converted to decimals. LBP index is the sum of the decimal numbers (Ojalaet al. 1996, 2002). Figure 2 shows the rotation invariant LBP for a 3*3 matrix and table 3 shows features which were extracted by use of LBP function.

- **Fuzzy local binary pattern (FLBP)**

Also In this method, after computing the histogram of the

Table 3. Features extracted from LBP and FLBP

Statistic	Formula
Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
Standard deviation	$std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$
Smoothness	$S = 1 - \frac{1}{1+\sigma^2}$
Kurtosis	$k = \frac{E(x-\mu)^4}{\sigma^4}$
Entropy	$E = -\sum_{i,j} c_{i,j} \times \log_2 c_{i,j}$
Skewness	$S = \frac{E(x-\mu)^3}{\sigma^3}$

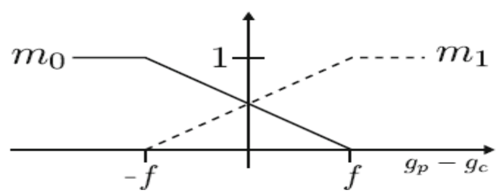

Figure 3. Membership function in FLBP. The x-axis is difference between gray level g_b-g_c and y-axis is function value.

possible pattern, one pixel position, may contribute to several bins of a histogram (Iakovidis et al., 2008). If g_b be the neighboring value and g_c be the center value, the difference between those, encodes with 3 values is:

$$m_0(p,f) = \begin{cases} 0, & g_p \geq g_c + f \\ \frac{f - g_p + g_c}{2 - f}, & g_c - f \leq g_p \leq g_c + f \\ 1, & \text{othrewise} \end{cases}$$

$$m_1(p,f) = 1 - m_0(p,f)$$

Where $f$is the interval fuzzy belonging. Membership function in FLBP, is shown in Figure 3.

The contribution for a pixel position (x,y) to a bin i in the histogram H is defined as bellow:

$$FLBP_{N,R(x,y,i)} = \prod_{p=0}^{N-1}[b_p(i)m_1(g_c - g_p) + (1 - b_p(i)m_0(g_c - g_p)]$$

$$H_{flbp}(i) = \sum_{x,y} FLBP_{N,R}(x,y,i)$$

Where p is the number of bits and $b_p(i) \in \{0,1\}$ is defined as the value of the pth bit of the binary representation of pattern$i$. Table 3 show five FLBP features which were extracted with by this function.

Data Analysis

Artificial Neural networks (ANN), particularly the multilayer Perception (MLP), are among the most practical. These networks are able to choose the appropriate number of layers and neurons, which aren't often too high, a nonlinear mapping arbitrary precision

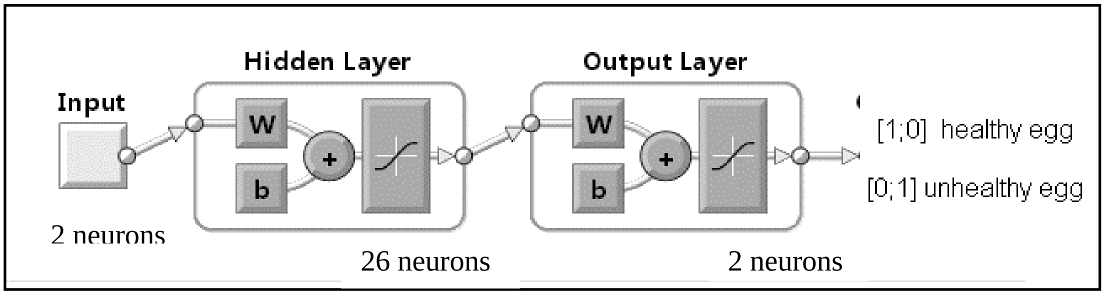

Figure 4. Schematic topologic for neural network.

Table 4. MLP architecture and training parameters

Architecture	Parameters	Training	Parameters
Number of layers	3	Initial weight and biases	Random
Number of neurons in each layers	Input: 29 Hidden: 20 Output: 2	Activation function	Tangent sigmoid
		Training parameter	Rule= Levenberg-Marquardt (trainlm)
		Performance	Mean Squared Error(MSE)
		Train function	Tangent sigmoid

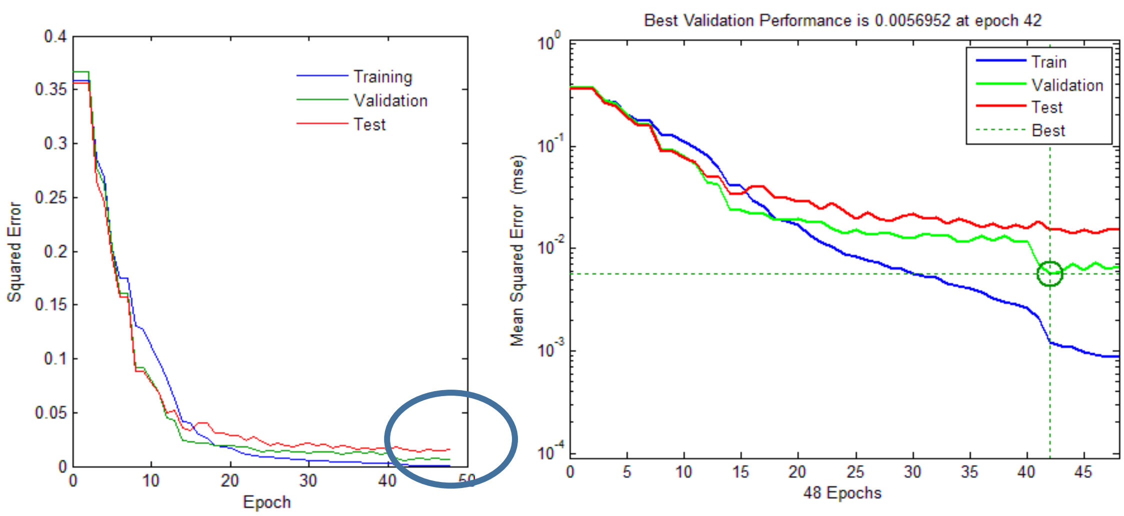

Figure 5. Trends of training, validation, and test errors as training iterations passes.

does. It is a linear model that used in various fields, such as pattern classification and detection. It is composed of elements such as the human brain. By comparing the output and the target of the network, the weights are adjusted. The schematic of neural network is shown in Figure 4.

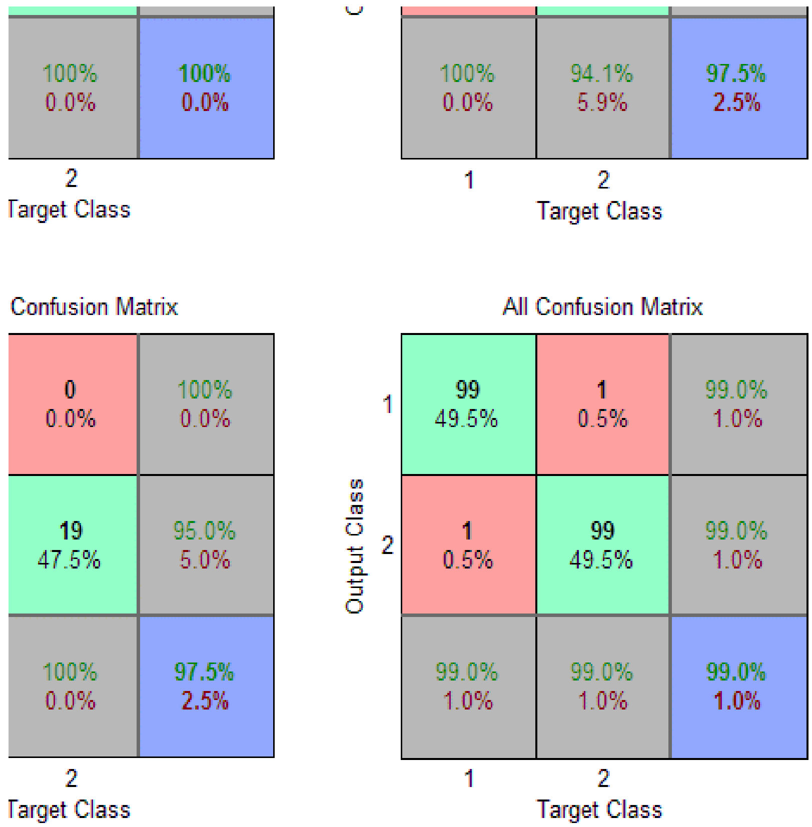

Figure 6

The trained network consists of three layers, Input, hidden and output layers. 26 features that had extracted from feature extraction phase were defined as an input vector. For hidden layer, 20 neurons was defined (it gets by examination) and at least, for output layer, 2 neurons were defined according to the dead ([0, 1]) and alive ([1,0]) fish eggs. For obtaining the best result, some adjustments must be applied. Table 4 shows some parameters of ANN architecture.

RESULT AND DISCUSSION

When the network started to train, over fitting was occurred. It is the tendency to memorize the training examples without learning how to generalize to new situations. To improve the network generalization, stop learning method is used. In this way the data divided into three categories: training, validation and testing. From the training data (160 samples) calculating the gradient and updating the weights and bias. Data validation (20 samples), with increase of error in these data, training become stop. The test data (20 samples), segmentation data quality checked. Figure 5 displays trends of training, validation, and test errors as training iterations passes.

Training stop occurs when the validation error starts to increase. It was at epoch 42 (Figure 5).Also confusion matrixes were used for showing the results (Figure 6). In that, diagonal cells show correctly cases and the off-diagonal cells show misclassified cases. It is determined from the matrix that the presented system is able to separate the alive and dead fish eggs from each other with 99% accuracy. Also, we can see from this matrix, accuracy of network for train, validation and test, separately. According to the mentioned results it was concluded that the developed algorithm (combination of the color and texture with artificial neural network) for quality assessment and distinguishing two types of dead and alive fish egg, has a very high efficiency.

CONCLUSION

Computer vision has the potential to become a vital component of automated food processing operations. The flexibility and nondestructive nature of this technique helps to maintain its attractiveness for application in various facets of the food industry. The evaluated features are color, shape, size, morphology, discoloration, and color intensity. These parameters allow for excluding faulty or substandard products. Advances in machine vision technology have made vision systems accurate, robust, and low cost which renders this system suitable for characterization of fish eggs quality evaluation. Recent application of machine system in the fish industry presented in this paper which was used to separate dead and alive fish eggs. Consider the obtained results it will be founded that this system coupled with ANN have a good potential to separate the alive and dead fish eggs with 99% accuracy.

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